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From neuronal to psychological noise – Long-range temporal correlations in EEG intrinsic activity reduce noise in internally-guided decision making

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ABSTRACT

Our personal internal preferences while making decisions are usually consistent. Recent psychological studies, however, show observable variability of internal criteria occurs by random noise. The neural correlates of said random noise - an instance of 'psychological noise' – yet remain unclear. Combining simulation, behavioral, and neural approaches, our study investigated the psychological and neural correlates of such random noise in our internal criteria during decision making. We applied well-established decision-making tasks which relied on either internal criteria - occupation choice task as internally-guided decision making (IDM) - or external criteria - salary judgment task as externally-guided decision making (EDM). Subjects underwent EEG for resting state and task-evoked activity during IDM and EDM. We measured resting state long-range temporal correlation (LRTC) in the alpha frequency range as the index of neuronal noise. Based on our simulation, we identified a measure of psychological noise (as distinguished from true preference change) in IDM. The main finding shows that the indices for psychological noise are directly related to frontocentral LRTC in the alpha range. Higher degrees of frontocentral LRTC, which index lower neuronal noise, were related to lower degrees of psychological noise during IDM. This was not found during EDM. Resting state LRTC was also related to task-evoked activity, such as conflict-related negativity, during IDM only. Taken together, our data demonstrate, for the first time, the direct relationship between neuronal noise in the brain's intrinsic activity and psychological noise in the internal criteria of our decision making.

1. Introduction

1.1. "Psychological noise" - decision making and the noise of its internal criteria

Decision making is a complex process that involves both external criteria associated with the stimulus itself and internal criteria related to the individual person. Paradigms guided by mainly internal criteria have been described as subjective preference judgment (Chen et al., 2010; Di Domenico et al., 2016; Di Domenico et al., 2015; Foo et al., 2014; Izuma et al., 2010), or, more generally, internally-guided decision making (IDM). This is distinguished from externally-guided decision making (EDM), the examples of which are gambling tasks and perceptual decision making (Boccia et al., 2016; Heekeren et al., 2004; Lieberman and Eisenberger, 2005; Meffert et al., 2013; Miyagi et al., 2017; Nakao et al., 2013a, 2013b; 2012; Volz et al., 2006; Wagner and Northoff, 2014).

While the internal criteria are supposedly consistent for each individual person, they may, nevertheless, be malleable and open to change. Observable variability of internal criteria occurs by random noise and learning effects (Fig. 1; Chen and Risen, 2010; Izuma and Murayama, 2013; Nakao et al., 2016). Such random noise can be determined as the random variation in IDM, or subjective rating, without any changes in the subject's true preference. Specifically, even if the subject prefers choice A to B, the subject may select occasionally choice B because the decision of its actual preference may be contaminated by noise (Chen and Risen, 2010; Izuma and Murayama, 2013).

In contrast to the noise, learning effects impact the internal preference itself. For instance, the phenomenon of choice-induced preference

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change shows that internal criteria are subject to change; the preference for a chosen item increases while it decreases for rejected items (Johansson et al., 2014; Koster et al., 2015; Miyagi et al., 2017; Nakamura and Kawabata, 2013; Sharot et al., 2012). Random noise, however, affects the subject's decision and subjective rating and thus what is observed as the learning effect (Chen and Risen, 2010; Izuma and Murayama, 2013). One can thus speak of "pseudo-preference change".

Taken together, tasks focusing on IDM must disentangle the effects of noise and learning. Although several paradigms have been proposed to disentangle the effects of learning from those of random noise (e.g., rate-rate-choice paradigm), there are currently no behavioral indices to assess the random noise in IDM. Simulation studies by Izuma and Murayama (2013) presupposed that random noise is contaminated in both the subjective rating (rating noise) and decision making (decision noise). These two sources of noise affect in opposing directions the pseud-preference change, measured as the difference between pre- and post-ratings (for precise relationships, see their Fig. 4). Given that, using a comparison between subjective pre- and post-ratings, even in the rate-rate choice paradigm, is not sufficient to identify random noise. Therefore, relying on simulation and behavioral studies, we first developed a 'proper' behavioral index for random noise in the internal criteria of our decision making including its distinction from learning effects.

1.2. *"Neuronal noise" - the brain's intrinsic activity and its long-range temporal correlation (LRTC)*

IDM and EDM have been related to different regions and electrophysiological markers in the brain. Cortical midline regions as part of the default-mode network (plays a special role in the brain's resting state activity) have been shown to be strongly involved in IDM, not EDM tasks (Nakao et al., 2012). Most interestingly, recent studies using EEG demonstrated that the resting state's power spectrum in the alpha band (8–13 Hz), and other frequencies, predicted task-evoked activity during IDM, but not EDM (Bai et al., 2016; Nakao et al., 2013b).

The central role of the alpha band in IDM is further supported by a recent study by Colosio et al. (2017), who conducted a choice-induced preference task and observed that the frontocentral resting-state alpha long-range temporal correlation (LRTC; see below) was directly related to the IDM. However, Colosio et al. (2017) did not take into account the effect from random psychological noise: their index of the learning effect, used in the correlation analysis with the LRTC, was contaminated by psychological noise (Chen and Risen, 2010; Izuma and Murayama, 2013). The relationship of psychological noise and/or the learning effect to the intrinsic brain activity in these studies remains unclear.

The brain's intrinsic activity can be characterized by a complex temporal structure consisting in LRTC (Hardstone et al., 2012; He, 2011; He et al., 2010; Huang et al., 2017; Linkenkaer-Hansen et al., 2001; Zhang et al., 2018). The LRTC can be measured by scale-free activity as in the detrended fluctuation analysis exponent (DFAe; Hardstone et al., 2012; Linkenkaer-Hansen et al., 2001; Peng et al., 1994; Zhigalov et al., 2015). Larger DFAe, within 0.5–1.0 reflects a high degree of auto-correlated time series and thus lower randomness (or noise) in neuronal activity (DFAe of white noise = 0.5). The LRTC have been shown to be relevant for various mental features like self (Huang et al., 2017) and consciousness (Tagliazucchi et al., 2016, 2013; Zhang et al., 2018) as well as for other features like prediction (Maniscalco et al., 2018), encoding (Honey et al., 2012), and movement sequencing including reaction time (Smit et al., 2013).

Since the learning effect in choice-induced preference change is an autocorrelated behavioral phenomenon (i.e., the probability of choosing a chosen item is increased and that of choosing a rejected item is decreased), the relationship between the LRTC of intrinsic brain activity and the learning effect (Colosio et al., 2017) is intuitively interesting. The intrinsic brain activity provides the basis for, and thus affects, task-related activities (called rest-stimulus interaction; Northoff et al., 2010 for review, Huang et al., 2017) Accordingly, the LRTC during resting-state appears to reflect the neural architecture to produce the autocorrelative IDM. At the same time, however, it remains an intriguing possibility that the lower random noise reflected in higher LRTC is related to the lower psychological noise in IDM. Actually, the brain's intrinsic activity's LRTC has been thought to reflect the intrinsic neuronal architecture contributing to the information integration across time and cortical regions to increase the signal to noise ratio in psychological tasks (Chaudhuri et al., 2015; Linkenkaer-Hansen et al., 2001; Ogawa and Komatsu, 2010; Palva et al., 2013; Smallwood et al., 2007). This still leaves open the role of the intrinsic activity's LRTC as an index of neuronal noise in decision making and, more specifically, the process by which it mediates the random noise of the internal criteria specifically during IDM. The main aim of our study was, therefore, to investigate resting-state LRTC in specifically the frontocentral alpha in EEG and to relate that to the behavioral indices of psychological noise in IDM (as identified in our simulation and behavioral studies).

1.3. *Aims and hypotheses*

The overall aim of our study was to investigate the relationship between psychological and neuronal effects of noise or randomness on the internal criteria during IDM. Specifically, we examined whether the EEG-based measure of neuronal noise in the brain's intrinsic activity, i.e., frontocentral LRTC in alpha range, is related to the degree of the random noise of the internal criteria in IDM (and EDM). Based on the above cited results on the link between LRTC and behavior, we hypothesized that higher degrees of LRTC on the neuronal level of the brain's intrinsic activity, reflecting less neuronal noise or randomness, are related to the degree of random noise during choice preference, specifically in IDM but not in EDM.

In the subsequent analyses, we first conducted simulations to establish behavioral measures to assess random noise as distinct from the learning effect during choice preference in IDM (and EDM). We distinguished three behavioral indices (mean decision consistency, rating-decision consistency, and change in decision consistency) to assess and differentiate the effects of random noise and learning (see Figs. 3 and 4). If LRTC is related to the psychological random noise in IDM, both the mean decision consistency and the rating-decision consistency would

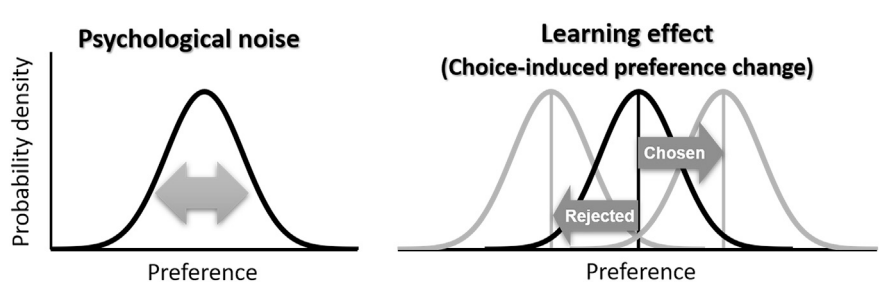

Fig. 1. Two types of variability in internal criteria. Normal curves represent the discretion of the participant's preference, which consisted of true preference and random noise for an item.

simultaneously show significant correlation with frontocentral alpha DFAe. In addition, if that relationship is specific to IDM, both the correlations for the mean decision consistency and the rating-decision consistency in IDM are expected to be significantly different from those in EDM. We focused on the frontocentral region, FCz, since that region is known to play a key role in choice-induced preference change and potentially psychological random noise effect (Colosio et al., 2017; Nakao et al., 2016).

In addition, to examine the reproducibility of the findings obtained by Colosio et al. (2017), we investigated whether the frontocentral alpha LRTC is related to the response-locked conflict-related negativity (CRN) during choice preference in IDM (and EDM). The amplitude of CRN is known to reflect the degree of conflict and has been reported (Di Domenico et al., 2016; Grützmann et al., 2014; Nakao et al., 2013a, 2010; 2009; Steinhauser and Yeung, 2010). Colosio et al. (2017) reported that the CRN during IDM correlated with both front-central alpha LRTC and choice-induced preference change indexed by the difference between post- and pre-ratings. Based on the findings reported by Colosio et al. (2017) and our previous study (Nakao et al., 2013a), we hypothesized that the intrinsic activity's LRTC, i.e., alpha band frontocentral DFAe, predicts task-evoked CRN specifically during IDM but not during EDM.

2. Materials & methods

2.1. Participants

This study examined 24 healthy undergraduate students (11 male; age range = 18–21 years, mean age = 19.58 years) recruited from Hiroshima University. All participants were native Japanese speakers, right-handed, with normal or corrected-to-normal vision. All were free of neurological and psychiatric disorders. No participant was either medicated or a habitual drinker or smoker. All experimental protocols were conducted in accordance with guidelines approved by the Ethical Committee of the Graduate School of Education, Hiroshima University. Written informed consent was obtained from each participant before the investigation. Each participant was paid a small fee for participation. After the preprocessing of resting state EEG, one participant was excluded because of excessive artifacts. Thus, a total of 23 participants (11 male; age range = 18–21 years, mean age = 19.57 years) were included in the resting state EEG analyses whereas 24 participants were included for the task data.

2.2. Stimuli

Details of the study protocol and the task procedure were described in (Nakao et al., 2016). In brief, the 28 occupation-related terms (e.g., lawyer, carpenter) were collected from the Classification of Occupation for Employment Security Service (ESCO: http://www.jil.go.jp/institute/seika/shokugyo/sakuin/). One term was chosen from each of the small classification of occupations in the ESCO. To determine the correct response of the EDM (salary judgment) task, the average annual salary for each occupation was collected from Nensyu-labo (http://nensyu-labo.com/2nd_syokugyou.htm), the salary data of which were based on a statistical survey by the Ministry of Health, Labor and Welfare of Japan. To avoid making the salary task (see below) difficult, we chose the occupation with a wider range of average annual salaries (see Supplemental material). In addition, we collected the usage frequency (the google hit number) of each word and confirmed that the usage frequency was not a covariate of the average annual salary (for more details, see Supplemental materials of Nakao et al. (2016)). For each participant and task, 112 pairs were generated randomly with the restriction that each term was used eight times.

2.3. Pre-experimental ratings of stimuli

Before conducting decision making tasks, participants were asked to rate the two dimensions (preference and salary) using a computer-based visual analog scale for all occupation words (see Fig. 1(a)). The following questions and scales were used for the ratings: Preference ("How much would you like to do the job?" 1 = not at all, 100 = very much) and salary ("How much pay is given for the following occupations?" 1 = very little, 100 = very much). The order used to rate these items was randomized across participants.

2.4. Decision making task – IDM and EDM

In the IDM (occupation preference judgment) task, the two occupation words were presented. Then participants were asked to judge which occupation they would rather do ("Which occupation would you rather do?") by pressing the button on the corresponding side, as in earlier studies (Di Domenico et al., 2016, 2015; Nakao et al., 2013a) (see Fig. 2(a)). Participants were explicitly instructed that no objectively correct answer exists: they must make their own decisions.

In the EDM (salary judgment) task, participants were asked to judge which is a highly paid occupation on average ("Which occupation is highly paid?") by pressing the button on the corresponding side (see Fig. 2(a)). Participants were instructed clearly that the average salary is based on the statistical survey by Ministry of Health, Labor and Welfare, and that there was one objective, correct answer. Following the method described by Akaishi et al. (2014), we did not present the visual feedback in the EDM task. We included the error trials of the salary task to calculate the behavioral indices and task-related brain activity since participants were not able to recognize the error trials without feedback and assumed that there were no error-specific responses in the cognitive and neuronal process.

2.5. Procedure

When participants arrived in the laboratory, the experimental procedure was explained. After electrode placement, participants were seated on a comfortable chair facing a computer screen in a quiet electrically shielded room. A chin rest was used to help participants maintain the head position during recording.

Participants performed eyes-closed (EC) baseline periods of 5 min. Participants were instructed to relax and allow their mind to disengage during these periods. After the resting state recording, participants completed the short questionnaire and provided pre-ratings for each occupation term. The short questionnaire included items asking whether they kept closing their eyes and whether they remained wakeful during the recording. All participants reported that they closed their eyes and had not slept during the recording.

Participants then performed two types of counterbalanced tasks. Four blocks of 28 trials were conducted for each task (Fig. 2(a)). The presentation side of words was randomized across participants. The order of trials was also randomized. Before the experimental trials, participants were given three practice trials for each task to familiarize them with the tasks. Each block began with the appearance of an instruction related to the task type on the screen for 3000 m s. After a 1000 m s blank, trials began. The fixation cross was presented for 1000 m s, then two stimulus words and a question ("Which occupation would you rather do?" or "Which occupation is highly paid?") were presented. The stimuli and question remained visible on the screen until 1500 m s after the participant pressed the button. The stimuli and question were replaced with the blank screen, which was presented for 1500 m s. While this blank screen was displayed, participants were allowed an eye blink. After this blank-screen period, the subsequent trial began (the fixation cross was presented for 1000 m s). The reaction time from the presentation of the stimuli to the response was recorded. Participants were instructed to press either the left or right button with the corresponding index finger as quickly and accurately as possible after each stimulus was presented. Additionally, they were asked to avoid eye blinking during times other than the blank screen.

2.6. Behavioral indices

To isolate the noise effect from learning effect, we used a combination of three behavioral indices (i.e., mean decision consistency, rating-decision consistency, and change in decision consistency). As we confirm in the simulation (Fig. 3), in case the effects of noise dominate, smaller noise produces higher mean decision consistency and rating-decision consistency but no change in decision consistency from the first to the last half of trials. If, in contrast, the learning effect dominates, the higher mean decision consistency, the lower rating-decision consistency, and the larger change in decision consistency are observed (see Fig. 4 for the summary of the relationships).

2.6.1. Decision consistency

To calculate the change in decision consistency and the mean decision consistency, we first calculated the decision consistency respectively for the first- and the last-half of trials (see Fig. 2(b)). The decision consistency represents the rate of trials in which a certain occupation word was repeatedly chosen or rejected. In cases where a participant chose an occupation in a certain trial and it was chosen again in the trial in which the occupation was presented the next time, we counted that trial as a consistent decision. In addition, in cases where a participant rejected an occupation in a certain trial and it was rejected again in the trial in which the occupation was presented the next time, we counted that trial as a consistent decision. The consistent decisions were counted for each occupation word. That number was then converted to a rate of the consistent decision by dividing the number of consistent decisions by the sum of the number of consistent and inconsistent decisions. The average of the rate of consistent decisions was calculated across all occupation words. That figure was used as the decision consistency.

2.6.2. Mean decision consistency

The total mean decision consistency across first and last half of trials is intuitively close to the concept of less decision noise (or, inversely put, consistency). Nevertheless, the index reflects both learning effect and less decision noise (Figs. 3(a) and Figure 4). Although this index by itself is not useful to distinguish the decision noise and learning effects, it can avoid the effect from the rating noise in a different way than the rating-decision consistency because pre-rating is not used to calculate this index (Fig. 2(b)).

2.6.3. Rating-decision consistency

The rating-decision consistency represents how often participants' decisions were consistent with pre-ratings of the same dimension (i.e., preference or salary). To calculate this index, we counted trials that are consistent between the rating value of each word stimulus and the judgment of the decision making task (Fig. 2(c)). For example, for a case in which the participant rated occupation A as 100 (very much) and occupation B as 1 (not at all) regarding one's preference, and chose occupation A (100) compared to B (1) in the IDM (occupational

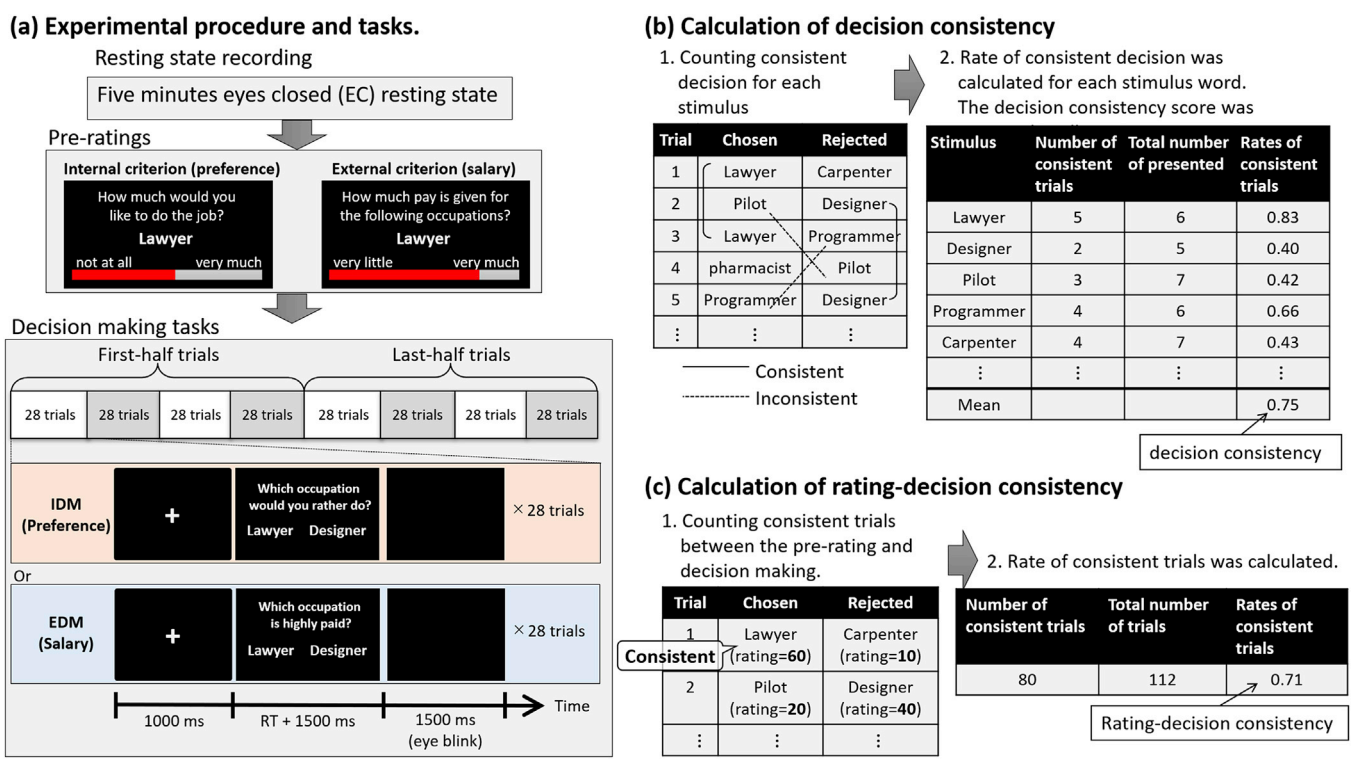

Fig. 2. (a) Experimental procedure and tasks. After the 5 min of resting state recording, participants were asked to rate the internal and external criteria (preference and salary) using a computer-based visual analog scale for all occupation words. As IDM and EDM tasks, we used occupation preference judgment for which no objectively correct answer exists, and salary judgment for which one objectively correct answer exists, respectively. Participants performed counterbalanced tasks of two types. RT denotes the reaction time. (b) Schematic figure of the calculation of decision consistency. The decision consistency represents the rate of trials in which a certain occupation word was chosen or rejected repeatedly. In cases where a participant chose Lawyer (first trial in the example of this figure) and it was chosen again in the trial in which Lawyer was presented the next time (third trial in this example), we counted that trial as a consistent decision. In addition, in cases where a participant rejected Designer (second trial in this example) and it was rejected again in the trial in which Designer was presented the next time (fifth trial in this example), we counted that trial as a consistent decision. The consistent decisions were counted for each occupation word. That number was then converted to a rate of the consistent decision by dividing the number of consistent decisions by the sum of the number of consistent and inconsistent decisions. The average of the rate of consistent decisions was calculated across all occupation words. (c) Schematic figure of the calculation of rating-decision consistency represents how often participants' decisions were consistent with pre-ratings of the same dimension (i.e., preference or salary). To calculate this index, we counted trials that are consistent between the rating value of each word stimulus and the judgment of the decision-making task. The sum number of consistent trials was divided by the total number of trials in each task.

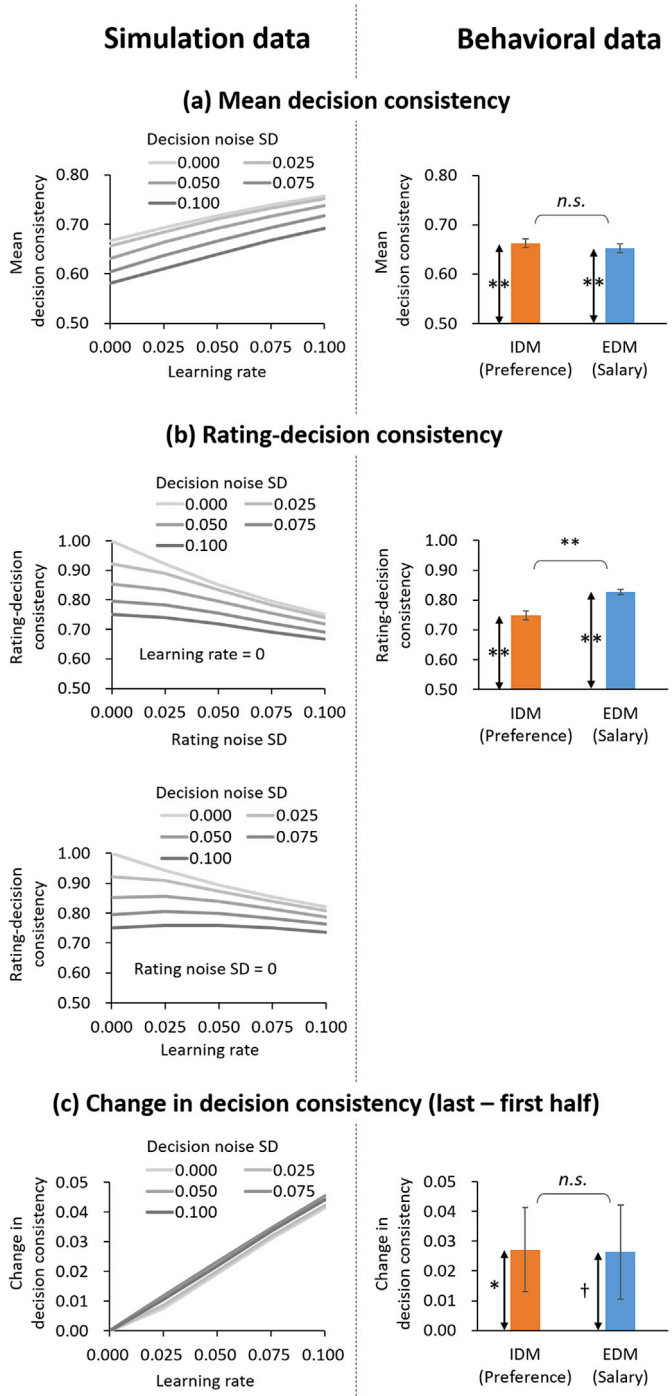

Fig. 3. Simulation data (left side) and behavioral data (right side) of the mean decision consistency (a), the rating-decision consistency (b), and the change in decision consistency (c). ** and * denotes significant difference ($p < .0001$ and $p < .05$, respectively), †denotes marginal difference ($p < .10$). Error bar shows standard error.

preference judgment), we counted the trial as consistent. The sum number of consistent trials was divided by the total number of trials in each task.

This index is decreased when true preference change occurs and increased when the decision and rating noise is small (Figs. 3(b) and Figure 4). Therefore, this index is useful to distinguish the noise and learning effects.

2.6.4. Change in decision consistency

The change (last minus first) of decision consistency predominantly reflects the learning effect rather than pseudo-preference change induced by the noises (Nakao et al., 2016, see also Fig. 3(c) of the present study).

2.7. Model simulation of behavioral indices

We conducted a simulation to clarify how the behavioral indices (i.e., rating-decision consistency, mean decision consistency, and change in decision consistency) react to the noise (i.e., the degree of noise-contaminated in pre-rating or decision) or the degree of true preference change by one's own choice (i.e., learning rate). In accordance with the approach employed by Nakao et al. (2016), we used a simple learning model representing learning effects (i.e., choice-induced preference change), which has been repeatedly reported in previous studies (Izuma et al., 2010; Miyagi et al., 2017; Nakamura and Kawabata, 2013). That is, the value (Q_i) of the chosen item was increased, whereas the value of the rejected item was decreased as follows (i is the index of the item; t is the index of the trial).

$$Q_i(t+1) = \begin{cases} Q_i(t) + \alpha \cdot (1 - Q_i(t)) & \text{if } i \text{ was chosen} \\ Q_i(t) + \alpha \cdot (0 - Q_i(t)) & \text{if } i \text{ was rejected} \end{cases}$$

Therein, α is the learning rate that determines how much the model updates the item value. α was varied from 0 to 0.1 at intervals of 0.025. The upper limit of α was 0.1 because the true preference change has been observed less than 1/10 of subjective rating scale in the previous studies using rate-rate choice paradigm (Colosio et al., 2017; Izuma et al., 2010) and blind choice paradigm (Miyagi et al., 2017; Nakamura and Kawabata, 2013). These paradigm can avoid the problem of the free choice paradigm (Chen and Risen, 2010; Izuma and Murayama, 2013). The range of the item value $Q_i(t)$ is restricted to values between 0 and 1. α is multiplied by $(0 - Q_i(t))$ or $(1 - Q_i(t))$ to restrict $Q_i(t+1)$ between 0 and 1, after updating the item value. Although α was multiplied by $(1 - Q_i(t))$ even when i was rejected in Nakao et al. (2016), it fails to limit the $Q_i(t+1)$ not smaller than 0. Hence, we modified the equation here.

The rating and decision noises were added when we conducted the simulation using a simple learning model. In the simulation, 24 hypothetical participants' data were generated: 28 word stimuli and 112 word pairs (trials) were used for our experiment (the same number as the number of trials of IDM or EDM, so four blocks of 28 trials). We first assigned a true preference to each word stimulus of each participant. By following Izuma and Murayama (2013) and Nakao et al. (2016), the true preference between 0 and 1 was assigned randomly by sampling from a normal distribution with mean 0.55 and standard deviation (*SD*) 0.1. To calculate rating-decision consistency, we added rating noise. For each participant and task, 112 pairs were generated randomly with the restriction that each term was used eight times as with our experiment. Then, a response series to 112 trials of decision task was generated: we added random noise (decision noise) to the true preference of each word stimulus. Words with higher (decision-noise contaminated) preference from word pairs were selected. Rating and decision noises were generated randomly from a normal distribution with mean 0 and *SD* 0, 0.025, 0.05, 0.075, or 0.1 the range of which generated the similar value of behavioral indices (mean decision consistency, rating-decision consistency, and change in decision consistency) with our behavioral data (see Fig. 3). We conducted 10,000 simulation iterations for each magnitude of noise and learning rate.

2.8. Division of conflict conditions

After the EEG experiment of each participant, we classified trials into two conflict conditions in each task using a chosen-frequency-based conflict division method (Nakao et al., 2013a, 2010, 2009). After the experiment, we counted the chosen frequency of each stimulus in each task. Then we classified trials into two conditions based on the

	Computational parameters		Behavioral indices			
			Previous study	Present study		
			Post-pre rating difference	Mean decision consistency *2	Rating-decision consistency *4	Change in decision consistency (last – first) *5
Noise effect	Rating noise	↘	↘ * 1	–*3	↗	–*3
	Decision noise	↘	↗ * 1	↗	↗	–
Learning effect	Learning rate	↗	↗	↗	↘	↗

Fig. 4. Summaries of the relationships between the computational parameters and behavioral indices. *1 Pseudo preference change. For the precise relationship, see Fig. 4 of Izuma and Murayama (2013). *2 See Fig. 3(a). *3 Pre-rating is not used to calculate decision consistency. See Fig. 2(b). *4 See Fig. 3(b). *5 See Fig. 3(c).

differences of the chosen frequency between the two stimuli of each pair. Stimulus pairs for which the difference of the chosen frequency was large were designated as the small-conflict condition. In contrast, those for which the difference of the chosen frequency was small were designated as the large-conflict condition. The trials were divided into the two conflict conditions in such a way that the difference of the number of trials between large-conflict and small-conflict conditions was minimal.

2.9. EEG recordings and pre-processing

EEG were recorded using 30 silver-silver chloride cup electrodes attached to an electrocap (Quik-Cap; NeuroScan), with electrodes placed at Fp1, Fp2, F7, F3, Fz, F4, F8, FT7, FC3, FCz, FC4, FT8, T7, C3, Cz, C4, T8, TP7, CP3, CPz, CP4, TP8, P7, P3, Pz, P4, P8, O1, Oz, and O2 according to extended International 10–10 Systems. The electrode impedance was maintained as less than 5 kΩ. The EEG signals were amplified with a bandpass of 0.0159–120 Hz and were digitized at a 1000 Hz sampling rate using an EEG recorder (EEG-1100; Nihon Kohden Corp., Tokyo, Japan).

Preprocessing of resting state EEG data was conducted by EEGLAB toolbox (Delorme and Makeig, 2004) running under Matlab 9.1.0 (The Mathworks Inc.). Data were down-sampled to 250 Hz, and were filtered using finite impulse response (FIR) filter with a low-pass of 60 Hz and a high-pass of 1 Hz. To remove bad channels and the non-stationary artifact by Artifact Subspace Reconstruction method (ASR; Mullen et al., 2015), we used 'clean_rawdata' EEGLAB plug-in. EEG data were re-referenced to an average reference. Independent component analysis (ICA) was used for the rejection of stationary artifacts (e.g., eye movement) from the EEG data. Adaptive Mixture of ICA (AMICA; Palmer et al., 2011) was conducted. After the noise components were rejected (see Supplementary material for the criteria to detect noise components), the remaining ICs were back-projected onto the scalp electrodes to obtain artifact-free EEG data. The EEG data were segmented into 30 s epochs with the 75% overlap.

Supplementary material provides more details of EEG recording and preprocessing.

2.10. DFAe and the confirmation of the measurement

Detrended fluctuation analysis was performed to quantify long-range temporal correlations (LRTC) by using Neurophysiological Biomarker Toolbox (NBT; Hardstone et al., 2012). For each artifact free 30 s epochs, alpha range (8–13 Hz) EEG time series was extracted by FIR filter. The amplitude envelope was calculated by the Hilbert transform, and the cumulative sum of the envelope was computed. Time windows of log-linearly increasing length from 1s to 30s were extracted with 0% overlap and each of those were linearly detrended using a least-squares fit. We here used 0% overlap since the epoch itself was extracted with the 75% overlap to increase signal noise ratio. The *SD* of the detrended data were calculated for each time windows, and the average of the *SD* across all the time windows of the same size from all epochs were computed as the fluctuation function, $F(t)$. The $F(t)$ was plotted for all time window sizes on logarithmic axes. The DFAe (i.e., the slope of the trend line in the 2–25-s range) was estimated by using linear regression (see Fig. 5). The DFAe between 0.5 and 1.0 indicates that the time series exhibit long-range temporal correlation.

To examine the reliability of the DFAe, the same numbers of available non-overlapping 30-s epochs were extracted from the first and last halves of 5-min recordings from each participant and were averaged respectively. The intraclass correlation coefficient (ICC, one-way random effects, absolute agreement, multiple measurements; McGraw and Wong, 1996) values were used to estimate the reliability of the present data. Furthermore, to examine whether DFAe reflects the non-random temporal structure of neural activity, we conducted surrogate data analyses (see Supplementary material).

The DFAe for the delta (1.5–4 Hz), theta (4–8 Hz), beta (13–30 Hz), and gamma (30–45 Hz) bands were also calculated and the correlation results were reported in the Supplementary material (Table S1).

2.11. Conflict-related negativity (CRN)

To examine whether the LRTC and behavioral indices are correlated with CRN amplitude difference between the large and small conflict conditions as with Nakao et al. (2009, 2010, 2013a, 2016) and Colosio et al. (2017), response-locked ERP was calculated for each decision making task and conflict condition. Artifact-free response-locked data, which was used to calculate response-locked beta-gamma power in Nakao et al. (2016), was applied for this analysis (see Nakao et al. (2016) for the details of the preprocessing of response-locked EEG). In brief, the response-locked data epochs starting from 1000 m s before and 1500 m s after the response button press were extracted. Baselines for event-related potential (ERP) were taken from −500 m s to −250 m s relative to the response onset. Independent component analysis (ICA) was used for artifact rejection from EEG data. After these artifact rejection processes, response-locked data was divided into large and small conflict conditions. The CRN was quantified as the averaged amplitude from 0 to 70 m s after response onset at FCz electrode, based on the method used in Nakao et al., 2010; Nakao et al., 2013a,b, 2009).

2.12. Correlation analyses

Spearman's correlation coefficient (*rho*) was used to avoid the effect of outliers. When we compare the two correlation coefficients, we applied the method of Hittner et al. (2003) and Zou (2007) using 'cocor' (http://comparingcorrelations.org/; Diedenhofen and Musch, 2015).

3. Results

3.1. Simulation results

The left side of Fig. 3 presents the mean results of 10,000 simulations. As shown in Fig. 3, our simulation results for all three measurements cover the range of behavioral data shown on the right side of Fig. 3. These results confirmed that the settings of the simulation (i.e., the ranges of decision noise and *SD*, rating noise and *SD*, and learning rate) were plausible.

For the mean decision consistency (Fig. 3(a)), the larger learning rate and smaller decision noise *SD* increases mean decision consistency. Regarding the rating-decision consistency (Fig. 3(b)), larger learning rate decreased the rating-decision consistency. In contrast, smaller decision and rating noise *SDs* increased rating-decision consistency. The change in decision consistency (Fig. 3 (c)) was predominantly affected by learning effect compared to the decision noise. This index was increased with the larger learning rate. Importantly, the decision noise does not increase the change in decision consistency when the learning rate is zero.

Together, our simulation results show differential effects of learning and random noise. High degrees of random noise yield higher degrees in both mean decision consistency and rating-decision consistency. In contrast, high degrees in the learning effect leads to the higher mean decision consistency, the lower rating-decision consistency, and the larger change in decision consistency (see Fig. 4 for summary). Accordingly, random noise and learning effects lead to opposite changes in specifically rating-decision consistency which is either increased (random noise) or decreased (learning effects).

3.2. Behavioral indices of noise and learning effects

The right side of Fig. 3 presents the results of three behavioral indices in IDM and EDM. For the mean decision consistency (Fig. 3(a)), we conducted one-tailed one-sample *t*-test against chance level (0.50) each for IDM and EDM, and revealed mean decision consistency was more than chance both in IDM ($t(23) = 18.07$, $p < .001$, lower-bound 95% CI = 0.65, $r = 0.97$) and EDM ($t(23) = 16.66$, $p < .001$, lower-bound 95% CI = 0.64, $r = 0.96$). No significant difference was found between IDM and EDM ($t(23) = 0.71$, $p = .49$, 95% CI = [-0.02, 0.04], $r = 0.15$, two-tailed paired *t*-test). These results suggest that participant decisions were not completely random both in IDM and EDM.

For rating-decision consistency (Fig. 3(b)), we conducted a one-tailed one-sample *t*-test against chance level (0.50) each for IDM and EDM, and revealed that rating-decision consistency was more than chance both in IDM ($t(23) = 17.14$, $p < .001$, lower-bound 95% CI = 0.72, $r = 0.96$) and EDM ($t(23) = 36.99$, $p < .001$, lower-bound 95% CI = 0.81, $r = 0.99$). In addition, EDM showed more rating-decision consistency than IDM ($t(23) = -4.81$, $p < .001$, 95% CI = [-0.11, −0.04], $r = 0.71$, two-tailed paired *t*-test). These results suggest that participants used internal or external criteria, respectively, for the IDM and EDM.

Regarding the change in decision consistency (Fig. 3(c)), we conducted one-tailed one-sample *t*-test against zero separately for IDM and EDM to examine whether the learning effect occurred, and revealed that the learning effect was observed both in IDM ($t(23) = 1.93$, $p = .03$, lower-bound 95% CI = 0.003, $r = 0.37$) and EDM ($t(23) = 1.68$, $p = .05$, lower-bound 95% CI = −0.0006, $r = 0.33$), though statistical significance for EDM was marginal. No significant difference was found between IDM and EDM ($t(23) = 0.03$, $p = .97$, 95% CI = [-0.05, 0.05], $r = 0.01$, two-tailed paired *t*-test).

Taken together, our behavioral results confirmed that the participants conducted IDM and EDM tasks based on internal or external criteria, respectively, and showed learning effects in both decision-making tasks.

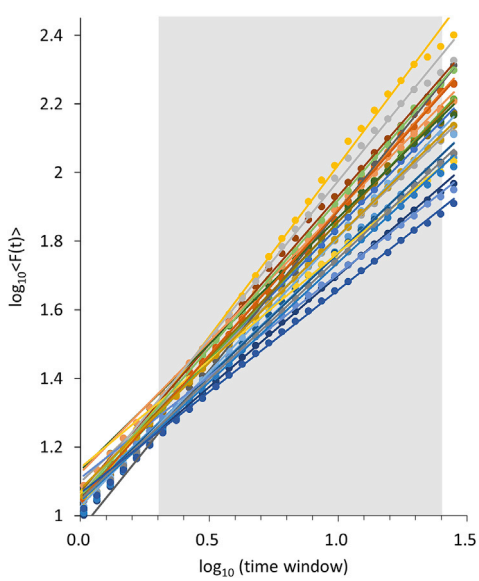

Fig. 5. A plot of the mean fluctuation function (*F*(t)) across scalp channels of alpha range (8–13 Hz) time series data of each time window size. The DFAe (detrended fluctuation analysis exponent) is the slope of the regression line. The color lines represent the trend lines using the data within the 2–25-s range (gray area) in each participant.

3.3. Resting state LRTC– DFAe

Fig. 5 shows the results of resting state alpha range DFAe at FCz. The average DFAe was 0.72 ($SD = 0.13$) at FCz. By following the approach proposed by Dimitriadis et al. (2013), to examine whether the DFAe of each participant has acceptable linearity, we assessed the F-statistics of the linear fits of the $\log_{10}<F(t)>$ over time ($\log_{10}$ time) for each participant. The regression analyses showed acceptable linear fits for all participants ($Fs(1,27)>6778$, $ps < 1 \times 10^{-15}$).

To estimate the reliability of DFAe in the present data, ICC (one-way random effects, absolute agreement, multiple measurements; McGraw and Wong, 1996) was calculated. The ICC of DFAe was acceptable (0.82, 95% CI = [0.58, 0.92]).

In addition, surrogated data analyses confirmed that the DFAe of the present data reflect non-random temporal structure but not the random variability of the amplitude (see the Supplemental materials).

3.4. Relationship between resting state LRTC and behavioral indices

3.4.1. Mean decision consistency

Fig. 6(a) shows the correlation between the mean decision consistency and the alpha DFAe at FCz. In IDM, the mean decision consistency was significantly positively correlated with alpha DFAe at FCz ($rho = 0.55$, $p = .007$, 95% CI = [0.18, 0.78]). In contrast, a marginal negative correlation was found in EDM ($rho = -0.37$, $p = .08$, 95% CI = [-0.68, 0.05]). The correlation coefficients were significantly different between the IDM and EDM ($z = 2.94$, $p = .003$, 95% CI = [0.34, 1.32]).

3.4.2. Rating-decision consistency

Fig. 6(b) shows the correlation between the rating-decision consistency and the alpha DFAe at FCz. In IDM, we found a significant correlation between the rating-decision consistency and the alpha DFAe at FCz ($rho = 0.42$, $p = .04$, 95% CI = [0.02, 0.71]). In contrast, no significant correlation was found in EDM ($rho = -0.21$, $p = .34$,95% CI = [-0.57,

0.22]). The correlation coefficients were significantly different between the IDM and EDM ($z = 2.35$, $p = .019$, 95% CI = [0.12, 1.07]).

3.4.3. Change in decision consistency

Fig. 6(c) shows the correlation between the change in decision consistency (last – first half trials) and alpha DFAe at FCz. No significant correlation was found in both the IDM (*rho* = −0.11; $p = .61$, 95% CI = [-0.50, 0.32]) and the EDM (*rho* = −0.009, $p = .97$, 95% CI = [-0.42,0.40]), and no significant difference between the correlation coefficients was found ($z = -0.30$, $p = .76$, 95% CI = [-0.71, 0.54]).

Taken together, the data show a statistically significant relationship of resting state alpha DFAe with both mean decision consistency and rating decision consistency during IDM (but not during EDM at FCz). In contrast, no correlation was observed between DFAe and change in decision consistency. Since the two correlations (i.e., correlations between the mean decision consistency and DFAe, and between the rating decision consistency and DFAe) were simultaneously significant, we accepted the hypothesis that the DFAe is related to the psychological random noise in the IDM (see also Fig. 4). These results strongly suggest that resting state alpha LRTC are related to random noise rather than learning effects in IDM. The specificity of the relationship in IDM was further supported by the significant differences between IDM and EDM tasks in the correlations between DFAe and mean decision consistency, and between DFAe and rating-decision consistency.

3.4.4. Negative correlations between EDM and DFAe at the centroparietal region

Although we focused on the frontocentral region, exploratory analyses for the mean decision consistency and the rating-decision consistency in EDM showed negative correlation at the centroparietal region (see Fig. 6; mean decision consistency, at CP4, *rho* = −0.62, $p = .001$, 95% CI = [-0.82, −0.28]; rating-decision consistency, at CPz, *rho* = −0.41, $p = .05$, 95% CI = [-0.70, 0.006]). Contrary to the case of IDM, these results suggest that the participants with lower LRTC at the centroparietal region during resting state showed higher consistency during EDM.

3.5. Relationship between resting state LRTC and task-evoked CRN

Fig. 7 (a) shows response-locked ERP at FCz in each conflict condition of IDM and EDM. As with the previous studies (Colosio et al., 2017; Nakao et al., 2013a, 2010, 2009), we observed larger CRN amplitude in the large conflict condition than the small conflict condition in IDM and EDM (main effect of conflict condition in two-way repeated-measures ANOVA (IDM, EDM × large, small conflict), $F(1,23) = 5.79$, $p = .02$, $\eta_G^2 = 0.03$). The one-tailed upper-bound 95% CI for CRN difference (large – small conflict) in IDM was −0.27, and that in EDM was −0.29. Regarding the stimulus-locked ERP, see Supplemental materials and Fig. S1.

Fig. 7 (b) shows the correlation between the CRN amplitude (large – small conflict conditions), and DFAe. In IDM, in results consistent with (Colosio et al., 2017), a significant correlation was found (*rho* = −0.41, $p = .03$, upper-bound 95% CI = −0.07, one-tailed). That is, individuals with larger alpha LRTC show a larger difference of CRN (large – small conflict conditions) at the same channel during the IDM. Interestingly, that relationship was not found in EDM (*rho* = 0.17, $p = .78$, upper-bound 95% CI = 0.49, one-tailed). The correlation coefficients were significantly different between the IDM and EDM ($z = -1.84$, $p = .03$, upper-bound 95% CI = 0.03, one-tailed).

4. Discussion

This study was undertaken to investigate the psychological and neuronal effects of random noise during choice preference in IDM. Our main finding is that, as established on simulation and behavioral studies, random noise on the psychological level of the internal criteria of decision making is directly related to the intrinsic activity's neuronal noise as indexed by frontocentral alpha LRTC. In short, we demonstrate for the first-time direct relationship between the intrinsic activity's neuronal noise and random noise on the psychological level of IDM (see Fig. 8 for a schematic summary).

4.1. Psychological noise - disentanglement between random noise and learning effects

We first conducted simulations to establish behavioral measurements for assessing random noise as distinct from the learning effect during choice preference in IDM (and EDM). Our simulation results (left side of Fig. 3) showed that the combinations of these indices allow one to assess the degree of noise and learning effects as summarized in Fig. 4.

The simulation model data show a clear differentiation between random noise and learning effects. If random noise is high, mean decision consistency and rating-decision consistency increase while the change in decision consistency (i.e., the difference between first and second half) shows no change. In contrast, high degrees of learning effects yield changes in all three indices, such as the higher mean decision

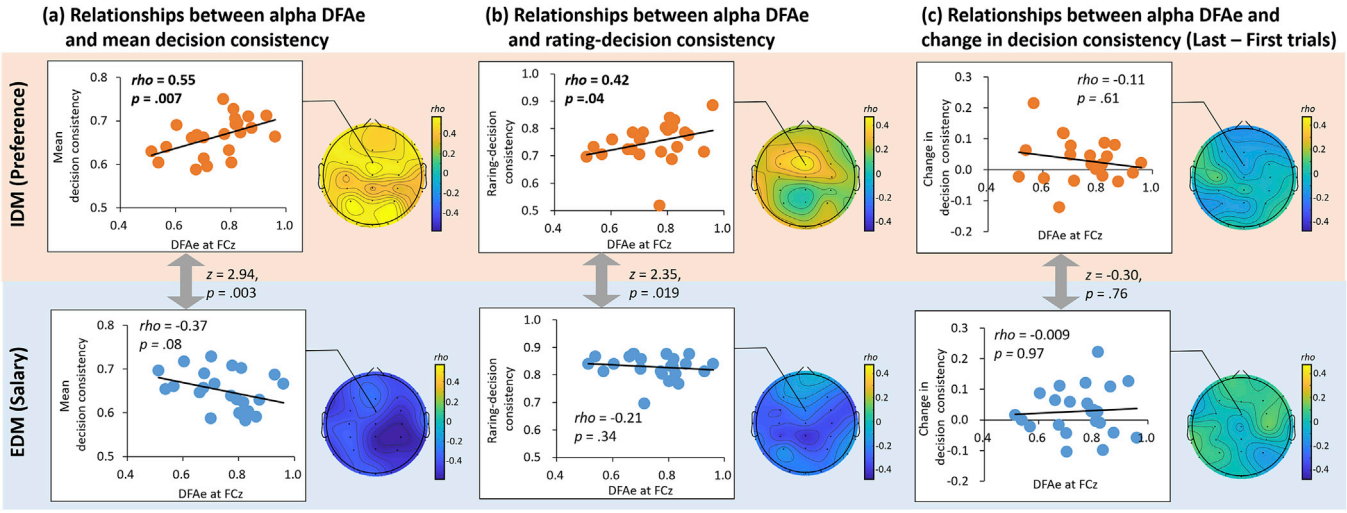

Fig. 6. Scatter plots and topo maps of rho between DFAe at FCz and three behavioral indices. The gray arrow and *z*-value represent the result of statistical comparison of correlations between the IDM and EDM.

consistency, lower rating-decision consistency, and higher change in decision consistency. Our behavioral data (right side of Fig. 3) confirmed the simulation results as the values and ranges of decision noise *SD*, rating noise *SD*, and learning rate were similar in both simulation and behavioral data.

We tested the three behavioral indices during IDM and EDM application in subjects. Our behavioral results confirmed that there are clear effects of both noise and learning during IDM and EDM. The change in decision consistency was above chance indicating similar degrees of learning effects in both IDM and EDM. The mean decision consistency and rating-decision consistency were also above chance in both IDM and EDM – this suggests that decision making was not completely random in either case. Only the rating-decision consistency differed significantly between IDM and EDM, with IDM showing higher scores in this index. This result suggests that the larger rating noise was contaminated more in the internal than external criteria.

4.2. From psychological to neuronal noise - intrinsic neural activity and IDM

After identifying the 'proper' behavioral index for random noise on the psychological level, we examined its relationship to neuronal noise in the brain's intrinsic activity. Specifically, we examined whether the intrinsic activity's LRTC in alpha range is related to the degree of the noise or leaning in both IDM and EDM.

We conducted correlation analyses between the LRTC and behavioral indices (Fig. 6). Consistent with our hypothesis, we observed that inter-individual variation in the intrinsic activity's LRTC positively correlated both with inter-individual differences in mean decision consistency and rating-decision consistency, simultaneously. In contrast, no such correlation could be observed for LRTC with the change in decision consistency.

Based on our simulation and behavioral data (Figs. 3 and 4), these results suggest that the LRTC correlated with the degree of the inter-individual variation of random noise in IDM but not its learning effects. If the LRTC were related to learning effects, one would have expected (i) a negative correlation of LRTC with the rating-decision consistency and (ii) a positive correlation of LRTC with the mean and the change in decision consistency. Neither was the case. Therefore, we claim that the intrinsic activity's alpha LRTC are related to random noise in IDM (rather than learning effects).

Taken together, our results demonstrate, for the first time, that the temporal structure (i.e., LRTC) of intrinsic brain activity, specifically its degree of neuronal noise as indexed by DFAe, predicts the degree of random noise that contaminates the internal criteria in our decision making, i.e., IDM (reversely, temporal consistency in IDM). Albeit tentatively, the intrinsic activity LRTC at frontocentral region can be seen to serve as a noise suppression mechanisms on the psychological level of IDM (see also Huang et al., 2017 for such interpretation of LRTC in the context of anesthesia). This is based on the notion that the intrinsic brain activity's LRTC reflects the neural circuit for integration of signals across time to increase the signal-noise ratio in tasks (Chaudhuri et al., 2015; Linkenkaer-Hansen et al., 2001; Ogawa and Komatsu, 2010; Palva et al., 2013). That, however, remains to be tested.

4.3. From psychological to neuronal noise – difference between IDM and EDM

Different from the case of IDM, the mean and rating-decision consistencies during EDM showed no significant correlation with DFAe at FCz, and the correlations were significantly different between the two decision-making tasks. Although we focused on the frontocentral region, the mean decision consistency and the rating-decision consistency in EDM showed negative correlation at the centroparietal region (see Fig. 6). Contrary to the case of IDM, these results suggest that the participants with lower LRTC at the centroparietal region during resting state showed higher consistency (i.e., lower psychological noise) during EDM. Although the neural and psychological mechanisms underlying the correlation remain to be elucidated, our results suggest that how the LRTC relates to the psychological noise is different between the internally or externally oriented tasks. Based on the simulation study showing the LRTC emerging on the basis of the balance of the number of inhibitory and excitatory connections in the neural network (Poil et al., 2012), the better balance of intrinsic-brain activity for less psychological noise during the task may depend on the differences in the types of psychological tasks (internally- or externally-oriented) and that of cortical regions.

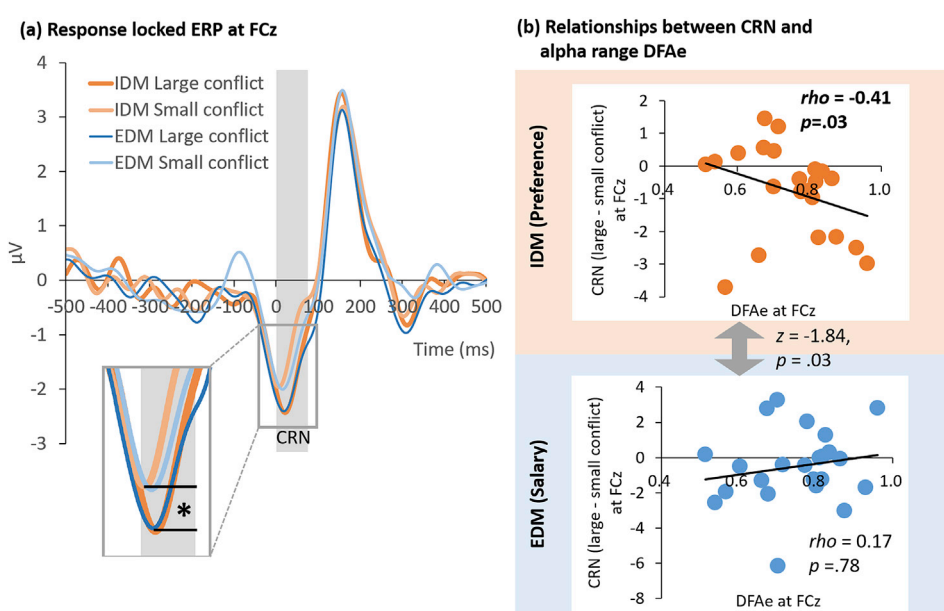

Fig. 7. (a) Response locked ERP for each task and conflict condition. (b) Correlations between CRN difference (large – small conflict) and resting state alpha DFAe at FCz.

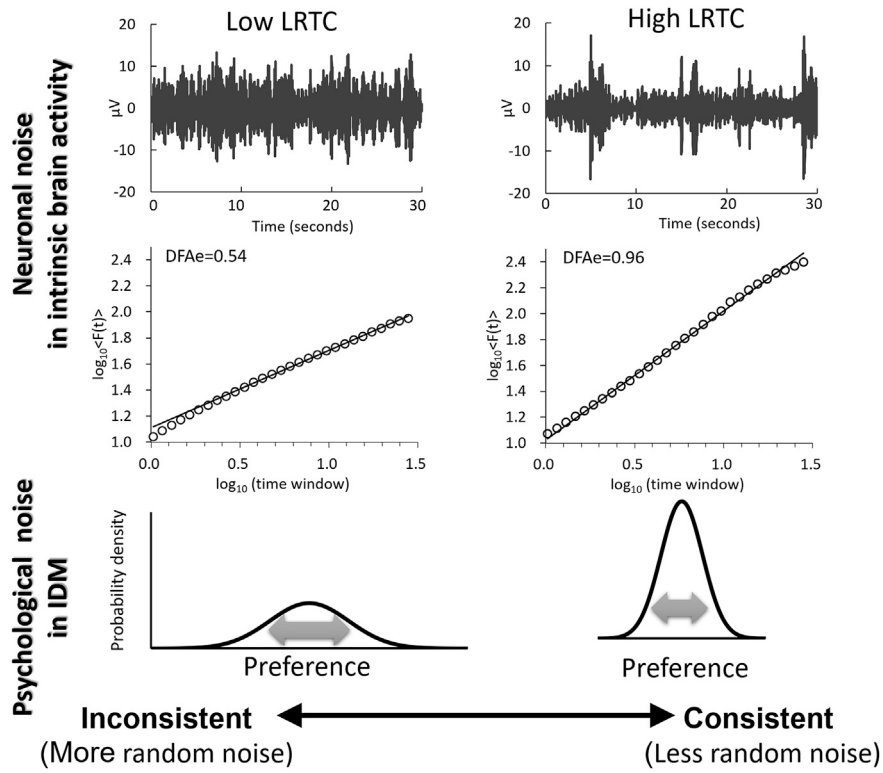

Fig. 8. Schematic figure of the main finding of the present study. The upper row shows the examples of the 30-s filtered EEG signal of 8–13 Hz at FCz from the participants with the lowest and highest LRTC. The middle row represents the DFAe fluctuation functions as with Fig. 5. The third row represents the schematic figures of psychological noise as with Fig. 1.

4.4. From neuronal noise to task-evoked activity - intrinsic neural activity and conflict detection

The central role of the intrinsic activity's LRTC in IDM was further confirmed by its impact on task-evoked activity, i.e., CRN. As expected and consistent with Colosio et al. (2017), the intrinsic activity's DFAe correlated with CRN in IDM. In addition, we showed that the relationship is specific for IDM; CRN in EDM showed no significant correlation with DFAe (Colosio et al., 2017 did not include EDM task). Neuronally, since the higher LRTC (i.e., less neuronal noise) in intrinsic brain activity reflects better information integration (Chaudhuri et al., 2015; Linkenkaer-Hansen et al., 2001; Ogawa and Komatsu, 2010; Palva et al., 2013), this result may indicate that better integration of intrinsic brain activity at the frontocentral region leads to better conflict detection, specifically during IDM. At the psychological level, internal criteria basically reflect self-knowledge and thus self-relatedness (Nakao et al., 2010, 2009; Northoff, 2016; Northoff et al., 2006), and our self may be central in suppressing random noise by integrating the information, as Sui and Humphreys (2015, 2016) proposed. Consequently, participants who have less random noise contaminated internal criteria would show better conflict detection during IDM. Consistent with this idea, we found a significant correlation for mean decision consistency in IDM ($rho = -0.34$, $p = .0499$, upper-bound of 95% CI = 0.02, one-tailed). Interestingly, that correlation was not found for EDM ($rho = -0.13$, $p = .27$, upper-bound of 95% CI = 0.18, one-tailed). The mechanism underlying the correlations, however, remains to be tested.

4.5. Limitations

One may wish to argue that we should conduct a computational model fitting which is used in the EDM studies (Bai et al., 2015; Katahira et al., 2017b; O'Doherty et al., 2007) instead of using the three behavioral indices. Indeed, the learning rate α, decision noise (inverse temperature β), and the values of each stimulus at every trial can be assessed by conducting the model fitting. Although we tried to apply model fitting to our data, results showed that the problem pointed out by Chen and Risen (2010) is extended to model fitting. That is, pseudo-learning effects occur as errors in parameter estimation and model selection in case the initial preference of the stimuli is not equal across all stimuli, as with occupation preference. The effect of initial preference to the parameter estimation is reported in Katahira et al. (2017a). Nevertheless, applying computational model analysis to IDM by overcoming that problem would be useful to estimate the precise learning rate α and the inverse temperature β representing less noise contaminated in internal criteria. Regarding the effect of initial preference to the three behavioral indices used in the present study, we confirmed that the individual variability of pre-rating across stimuli is neither significantly correlated with the three behavioral indices nor with the DFAe (see Supplemental materials, Table S2).

We did not apply the standard tasks for EDM in our paradigm such as reward decision making tasks, perceptual decision making tasks, etc. (Doya, 2008; Heekeren et al., 2004; Nakao et al., 2012; O'Doherty, 2004). That was due to the main aim in our paper of studying internal criteria rather than external criteria, and thus IDM rather than EDM. To properly control for IDM, that made necessary the development of a novel EDM task which we validated in various previous studies (Nakao et al., 2016, 2013a). However, several studies reported correlation between the LRTC and performance of perceptual decision making (Palva et al., 2013; Sangiuliano Intra et al., 2018). Future studies may wish to compare the here applied IDM and EDM tasks with the typical EDM tasks in the literature.

In addition to other EDM, one may also want to investigate other ways of formalizing the learning effect in IDM. For instance, one may want to use other paradigms, such as rate-rate-choice paradigm and/or blind choice paradigm, which can use the difference of pre-post subjective preference ratings without suffering from the problems as the here used

free choice paradigms. That remains to be tested.

It should be noted that our results are based on a limited number of stimulus words (occupations), and the participants were young Japanese students. The contents and structure of self-knowledge as internal criteria (Nakao et al., 2010, 2009) are thought to be different between eastern Asian (Collectivism) and Western (Individualism) cultures (Chiao et al., 2008; Markus and Kitayama, 1991). That difference would likely have a significant impact on the manner of career choices, IDM. We confirmed reproductivity of the mean and the change in decision consistencies by using the dataset of the previous study (Nakao et al., 2013a) that was conducted in Canada by a using different word set (see Supplemental materials). To expand the generalizability of the present results to the western culture, however, we need to re-examine the correlations between the behavioral measurements and DFAe by using the other word stimuli and participants from the European or North American cultures. Though not related to the cultural difference, in regard to generalizability, we examined the impact of gender on the present results. The mean decision consistency was different between the gender but the correlation results with the mean decision consistency were retained after excluding the effect of gender (see Supplemental materials for more details).

5. Conclusion

We here demonstrate that the intrinsic activity's neuronal noise, as indexed by its alpha LRTC, is directly related to random noise on the psychological level in the internal criteria of decision making. The combined simulation, behavioral, and neuronal approaches in our study allowed to identify the 'proper' behavioral index of random noise on the psychological level, which could then be linked to neuronal noise, i.e., LRTC. Our data show, for the first time, that the intrinsic activity's LRTC may be central in reducing random noise on the psychological level of decision making, i.e., IDM. Accordingly, though tentative, our results suggest that the intrinsic activity's LRTC serves as a noise suppression mechanism at the psychological level. Less noise in the intrinsic activity, as indexed by higher LRTC, may lead to lower degrees of random noise on the psychological level of IDM.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.neuroimage.2019.116015.

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